

Pallas: HPC Trace analysis at scale

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gitlab.inria.fr/pallas/pallas



Context: performance analysis at exascale

Investigating performance problems

- Many sources of performance problems at scale
 - Collective communication, load imbalance, network contention, NUMA effects, ...
- Finding a bottleneck requires investigation
 - Run the application once, analyze its execution trace
- Applications mix programming models (MPI+OpenMP, MPI+CUDA), and libraries (StarPU, netcdf, Pytorch, ...)
- **Need for generic, modifiable tracing tools**



Analyzing huge performance data

Finding the needle in the haystack

- Traces are **records of execution** made for **post-mortem analysis**
 - Store vast amount of detailed information
 - Require a lot of processing before being useful
- Trace analysis resources scale with trace size
 - Gets worse with execution time and # of threads
- HPC applications have **recurring patterns**
 - If leveraged, would yield **fast, scalable analysis**

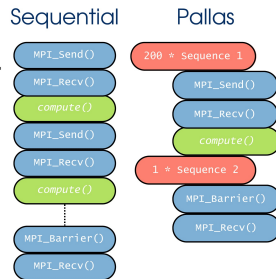
Proposal: Pallas trace format

Detecting repetitions at runtime

- Functions are **grouped by call signature** as Tokens.
- **Repetition of Tokens** are stored as loops
- **Durations and timestamps** are stored in buckets with **statistics** for **fast data retrieval**

A new trace format ?

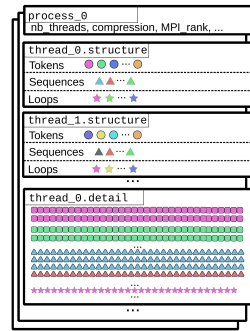
- Fully **generic** trace format
- **OTF2** and **Python** API for compatibility
- Set of basic analyses provided
 - Communication matrix
 - Contention¹ detection
 - Histogram plotting
 - Visualisation



Analysis-optimized trace storage

Separating data from metadata

- One folder per thread
- Header file with general information
 - Grammar / Function names
 - Runtime statistics
- Specialized files contain analysis data
 - Easily removable
 - On-demand loading



Evaluations

Comparison between:

- **EZTrace / OTF2** (no pattern detection)
- **EZTrace / Pallas** (with our OTF2 API)
- **Pilgrim²** (perfect pattern detection)

Ran 5x, **4096 MPI nodes** (Jean-Zay, Idriis)

Trace size:

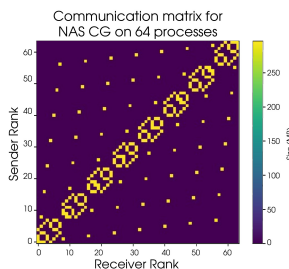
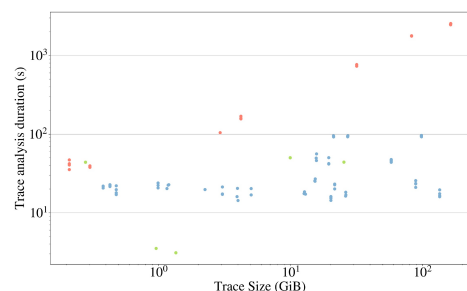
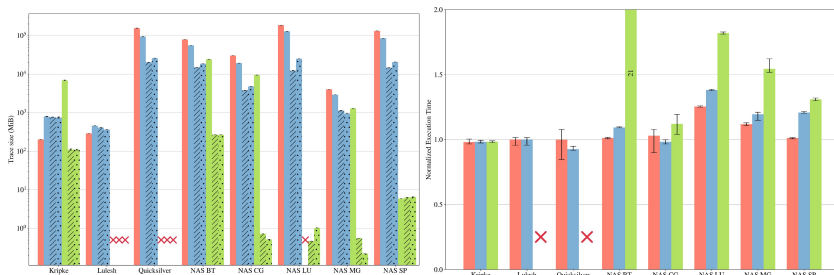
- OTF2 generates the biggest traces
- Pallas stores more information than Pilgrim
- Pilgrim has great compression
 - **Tends to crash due to OOM**
 - Needs to decompress everything when reading

Runtime overhead:

- OTF2 and Pallas both have **low overhead**
- Pilgrim adds **significant** overhead

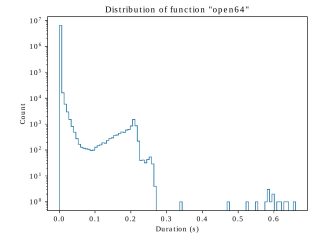
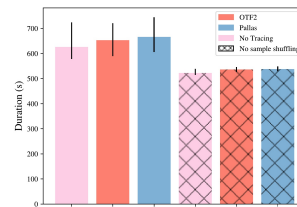
Case-study: ResNet50 / ImageNet

- Deep-learning application with known³ I/O contention issue
- **128 MPI processes** on the GPU partition of Jean-Zay
- Traced **MPI, I/O and Python** functions using EZTrace
 - Compared OTF2 and Pallas
 - **Pilgrim does not provide a proper reading API**
- Analysis process in 3 steps:
 - Identify the most time-consuming functions
 - Histogram these functions to identify issues
 - Compute a contention score



Communication matrix plotting:

- OTF2 scales linearly with trace size
 - The whole trace needs to be parsed
- Pallas and Pilgrim have **near-constant analysis time**
 - Only the grammar is read



Metric	OTF2	PALLAS
Performance overhead	4.2 %	6.4 %
Number of collected events	428,415,180	429,008,944
Number of files	21,003	42,255
Total trace size	6.1 GiB	1.4 GiB
Time to profile	40.46 s	8.37 s
Time to compute histograms	1285.34 s	144.67 s
Time to estimate contention	40.46 s	7.93 s

Ongoing work

- Improve analysis API (Python, R)
- Improve tracing performance, trace visualization
- Scaling :
 - *Horizontally*: Longer execution times
 - *Vertically*: More threads / processes
 - *Analysis*: TBs of data in a few seconds